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Development of Neural Network Model of Disc Brake Operation

The quality of artificial neural network models mostly depends on a proper setting of neural network architecture i.e. learning algorithm, transfer functions, range and distribution of data used for training, validation, and testing, etc. The goal of this paper is related to the investigation on how artificial neural network architectures influence the network's generalization performance based on the same input/output parameters. The complex procedure of an artificial neural network model development has been demonstrated related to the disc brake performance. The influence of disc brake operation conditions (application pressure, initial speed, and temperature) has been modelled related to the disc brake cold, fade, and recovery performance. The artificial neural network model has been developed through investigation of how the synergy of different network's parameters, such as learning algorithm, transfer functions, the number of neurons in the hidden layers, affect the neural model abilities to predict the disc brake performance. It was shown in this paper that complex non-linear interrelations between the disc brake input/output variables can be modelled by proper analysis and setting of artificial neural network parameters.

Keywords: artificial neural network, disc brake, performance, neural modelling.

1. INTRODUCTION

One of the most powerful tools of artificial intelligence has emerged under the name of artificial neural networks, which mimic the function of the human brain [1]. In the last decade, artificial neural networks have emerged as attractive tools for modelling of nonlinear process, especially in situations where the development of phenomenological or conventional regression models becomes impractical or cumbersome [2]. Artificial neural networks could be adequately characterized as a computer modelling approach with particular properties such as the ability to adapt to a changing environment or learn from examples through iterations without requiring a prior knowledge of the relationships of process parameters [2]. Moreover, artificial neural networks have great capabilities to generalize, cluster or organize data, deal with uncertainties, noisy data, and non-linear relationships [3]. Artificial neural networks are composed of simple elements operating in parallel, called artificial neurons [4,5]. As in nature, the connections between artificial neurons (connection weights) largely determine the network function [5-7]. A neural network can be trained to perform a particular function by adjusting the values of the connections (weights) between elements. According to [8], a neural network resembles the brain in two respects: (i) knowledge is acquired through a learning process, and (ii) connection strengths between neurons, known as synaptic weights, are used to store the knowledge.

Typically, neural networks are adjusted, or trained, so that a particular input leads to a specific target output (i.e. network predictions).

The artificial neurons are grouped into layers. Input layer receives data from outside of the network, while output layer contains data representing the network predictions. Layers between these two kinds of layers are called hidden layers. When using multilayer neural networks for solving a problem, number of neurons in the hidden layers is one of the most important issues [9,10]. It is known that insufficient number of neurons in the hidden layers leads to the inability of neural networks to solve the problem while on the other side too many neurons leads to overfitting and decreasing of network generalization capabilities. To describe a neural network's architecture adequately, it is necessary to specify how many layers it has, each layer's transfer function, the number of neurons in each of them and to characterize how layers are interrelated [8,11-14].

Since the quality of artificial neural models depends on a proper setting of a neural network architecture and other influential parameters (training algorithm, for example), the main goal of this paper is related to the investigation on how network's architecture variation influences its generalization performance (for a given data set). It would be demonstrated by modelling of the disc brake performance.

Neural modelling of automotive disc brake performance has been done versus changes of the disc brake's operating conditions. Based on the analysis of how each neural network parameter influences the final neural model prediction abilities, a proper selection of artificial neural network parameters was done. It provided that properties of the neural model of disc

brake operation can be tuned in order to improve its prediction abilities.

2. NEURAL NETWORK MODELLING

The process of a neural network model developing, especially in the case when very complex functional relationships need to be modelled, includes resolving of very important issues. According to that, to develop the neural model able to predict disc brake's performance, versus different brake operation regimes, the following steps were necessary to be done: (i) identify input and output data, (ii) select data generator, (iii) data generation, (iv) data pre-processing, (v) neural network architectures and training algorithms selection, (vi) training of the neural networks, (vii) accuracy evaluation, and (viii) the neural model testing. The synergistic influence of above mentioned parameters needs to be analysed, in order to make a proper selection of the neural network parameters.

Identification of neural model's input and output, whose functional relationship should be modelled, represents the first important step in the neural model developing. It primarily depends on model objectives and choice of the data generator [7,12]. In this case, the input parameters are defined by the disc brake operation conditions (initial speed, application pressure, and brake interface temperature). On the other side, the braking torque has been taken as an output parameter (see Figure 1). The general concept of an artificial neural network model is shown in Figure 1. Artificial neural network has to be trained with corresponding data in order to learn the functional relationships between input/output data pairs. In order to be trained, the data for neural network training should be generated. The type of data generator depends on the application and the availability [8].
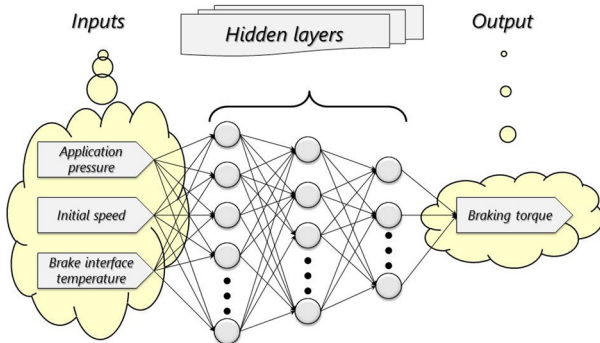

Figure 1. Artificial neural network input/output parameters

In this case, as a data generator, single-end full-scale inertia dynamometer has been used. The testing of the disc brake has been performed under strictly controlled conditions related to changes of the application pressure, initial speed, brake interface temperature, and inertia of revolving masses. The role of data generator is important from the point of view of repeatability of the testing conditions in order to establish the relationships between input and output parameters space. In order to provide data for artificial neural networks training and testing, the disc brake has been tested according to the adopted testing methodology (see Table 1).

The testing methodology was selected based on the range and distribution of data that were going to be used for training and testing. Regarding Table 1, it can be seen that eight different tests have been used in order to collect all necessary data for neural network's training. These tests have been divided as follows: (i) cold performance 1, 2, 3, and 4 (ii) fade performance 1 and 2 (iii) recovery performance 1 and 2. At the beginning, the tested disc brake has been subjected to burnishing process (see Table 1). To develop the best neural network model, able to predict a complex synergy of influences of disc brake operation conditions, the total number of data presented to network may be divided into three sets (the training data set, validation data set, and test data set) [9,15]. Training data set is used to guide the training process (i.e. update the network weights). According to [12,13,15,16], the number of training data pairs has significant influence on network's generalization capabilities. The number of training data pairs should be at least several times larger than the appropriate network's capacity. Validation data set is used to monitor the quality of neural network model training and to indicate when to terminate the training process. Test data set is used to examine the final quality of the developed neural model and to evaluate its generalization and prediction capabilities.

The main purpose of artificial neural networks training is to minimize the error between desired and actual output data values. Moreover, the abilities of neural network to extend its prediction capabilities outside the training data set is of essential importance for implementation of artificial neural networks method to predict disc brake performance.

The artificial neural network architecture, which represents the model potential prediction abilities in synergy with others network parameters, is unknown in advance. That is why the number of different

Table 1. Testing methodology

Test No.	Test	Pressure [bar]	Initial speed [km/h]	Temperature [°C]	No. braking
1	Burnishing	40	90	< 100	100
2	Cold performance (1), (2)	20 – 100	20 – 100	< 100	50
3	Fading (1), (2)	Correspond to the 3 m/s^2 deceleration on first braking	90	Open	30
4	Recovery performance (1), (2)	20 – 100	20 – 100	Reached after 3 min cooling under 300 rpm after fading test	50
5	Cold performance (3), (4)	20 – 100	20 – 100	< 100	50
Total number of brakings					205

The artificial neural network architecture, which represents the model potential prediction abilities in synergy with other network parameters, is unknown in advance. That is why the number of different architectures should be analyzed. Therefore, it is necessary to properly determine the neural network construction together with appropriate learning algorithm that shows the best prediction results. Different variations of network structures can be obtained through varying of the number of hidden layers and the number of neurons in each of them. According to [6], the balance between the size of training, validation, and test data set, should be optimally resolved.

The total number of input/output pairs, collected by disc brake testing according to adopted testing methodology was 205 (see Table 1). It means that 205 input/output pairs were available for the neural networks training, validation, and testing. Since the strategy of data dividing in two sets has been chosen, 155 input/output data pairs have been used for neural networks' training and 50 pairs for their testing (see Table 2).

Table 2. Input/output data splitting

Test No.	Test	Data splitting	
		Training	Testing
1	Burnishing	25	–
2	Cold performance (1)	25	–
3	Fading (1)	15	–
4	Recovery performance (1)	25	–
5	Cold performance (2)	25	–
6	Cold performance (3)	25	–
7	Fading (2)	5	10
8	Recovery performance (2)	10	15
9	Cold performance (4)	–	25
	Total	155	50

Neural networks can be trained more quickly if the input and output data have been firstly subjected to pre-processing [8,9,17]. By scaling of training data pairs within a certain range, all weighted relations in the neural network may remain in the small, predictable, range. Furthermore, the performance of neural networks could be improved. The data can be scaled in different manners. In this case, the linear scaling has been performed according to the (1).

$$\bar{x} = \bar{x}_{\min} + \frac{x - \bar{x}_{\min}}{\bar{x}_{\max} - \bar{x}_{\min}}(\bar{x}_{\max} - \bar{x}_{\min}) . \quad (1)$$

According to (2), initial speed, application pressure, and brake interface temperature have been scaled in the range of 0 to 0.5).

$$I_{\text{scal}} = \frac{I_{\text{curr}} - I_{\max}}{I_{\max} - I_{\min}} \cdot 0.5 \quad (2)$$

where corresponding indexes are related to: I_{curr} – current input value, $I_{\max}$ – maximum input value, and $I_{\min}$ –minimum input value.

On the other hand, target parameter (i.e. braking torque) was also linearized using (1). It should be noted that by varying the difference in brackets (see (1)), the range of data distribution can be increased or decreased. In that way, the network prediction performance can be tuned by adjusting of the scaled data range. Braking torque linearization was done by (3).

$$T_{\text{lin}} = 0.5 + \frac{(T_{\text{curr}} - T_{\max})}{(T_{\max} - T_{\min})} \cdot 0.1 \quad (3)$$

where corresponding indexes are related to: T_{curr} – current target value, $T_{\max}$ – maximum target value, and $T_{\min}$ – minimum target value.

In this paper, according to the above proposed strategy for varying of different network architectures and based on the program package MatLab 7.5.0.342 (R2007b) the following network structures have been investigated:

- One-layered structures: 3 [1]$_1$ 1, 3 [2]$_1$ 1, 3 [3]$_1$ 1, 3 [5]$_1$ 1, 3 [8]$_1$ 1 and 3 [10]$_1$ 1;
- Two-layered structures: 3 [1-1]$_2$ 1, 3 [2-2]$_2$ 1, 3 [3-2]$_2$ 1, 3 [5-2]$_2$ 1, 3 [8-4]$_2$ 1 and 3 [10-4]$_2$ 1;
- Three-layered structures: 3 [2-2-2]$_3$ 1, 3 [3-2-2]$_3$ 1, 3 [4-3-2]$_3$ 1, 3 [5-3-2]$_3$ 1, 3 [8-3-2]$_3$ 1 and 3 [8-4-2]$_3$ 1.

Each one of these 18 different network architectures have been trained with six different training algorithms: Levenberg-Marquardt (LM), Bayesian Regulation (BR), Resilient Backpropagation (RP), Scaled Conjugate Gradient (SCG), Gradient Decent (GDX) and Quasi-Newton (BFG), respectively. In accordance with (4), the sigmoid activation function has been used between the input and hidden layers and between the hidden layers.

$$f(x) = \frac{1}{1 + e^{-x}} . \quad (4)$$

In addition, a linear activation function has been used between hidden and output layer (see (5)).

$$f(x) = x . \quad (5)$$

3. RESULTS AND DISCUSSION

Since 108 neural models of the disc brake operation have been developed, these neural models have been tested versus data stored in the test data set. The quality of prediction of such obtained neural models might be evaluated by observing the difference (in percentage) between predicted and real values. Accordingly, several error intervals may be established. The prediction performance of different artificial network architectures has been analyzed versus influence of used learning algorithm. The six error intervals that have been established (0 – 5 %; 5 – 10 %; 10 – 15 %; 15 – 20 %; 20 – 25 %; 25 – 30 %). The number of the predicted results, which belong to each of these error intervals, have been calculated and expressed as a fraction of the test data set (in percentage).

Based on the networks' predictive capabilities, it is possible to find which network architecture shows the best prediction results versus influence of the learning

algorithm. The total number of 108 different neural models have been tested (18 different neural networks in combination with the 6 learning algorithms) to evaluate their capabilities for generalizing the disc brake performance under different operation conditions.

The influence of Levenberg-Marquardt learning algorithm on the neural networks prediction abilities is shown in Figure 2. It can be seen that the all considered neural networks are extremely sensitive to the number of neurons in the hidden layer. By increasing the number of neurons in the hidden layer, from 1 to 5, the quality of prediction, in the first error interval (0 – 5 %), has been improved for all network architectures. With further increasing of the number of neurons in the first hidden layer, from 8 to 10, predictive abilities of all networks have been decreased (except for the network 3 $[8\text{-}3\text{-}2]_3$ 1). This means that in the case of Levenberg-Marquardt training algorithm too many neurons in the first hidden layer are not desirable for input/output data mapping.

The number of neurons in the two-layered neural network structures has been varied in the first hidden layer between 1 and 10. On the other hand, that number of neurons in the second hidden layer has been kept on 2, except for the networks 3 $[8\text{-}4]_2$ 1 and 3 $[10\text{-}4]_2$ 1. As it can be seen in Figure 2, the three-layered network structure 3 $[8\text{-}3\text{-}2]_3$ 1 shown the best prediction capabilities.

In the case when the artificial neural networks (one, two, and three-layered) have been trained by Bayesian Regulation algorithm (see Figure 3), the prediction capabilities of adopted network architectures were different than those shown in Figure 2. It can be seen that all considered network structures are non-sensitive to variation of the number in hidden layers. Furthermore, it is also evident (Fig. 3) that variation of the number of neurons in each hidden layer did not cause instability in the neural networks prediction. The quality of prediction in the first error interval (0 – 5 %) is still very satisfactory in the case of one-layered network structures with 3, 5, 8 and 10 neurons in the hidden layer. In the case of training with Levenberg-Marquardt algorithm, the one-layered and two-layered networks with minimal number of neurons in the hidden layers (3 $[1]_1$ 1 and 3 $[1\text{-}1]_2$ 1) have shown less precise prediction results. Obviously, according to Figures 2 and 3, the networks trained by Bayesian Regulation algorithm shown better prediction of the disc brake performance compared to the networks trained by Levenberg-Marquardt algorithm. The two-layered and three-layered network structures showing high prediction performance (see Figure 3). The three-layered network architecture 3 $[2\text{-}2\text{-}2]_3$ 1 has shown the best prediction results. As it can be seen by Figures 2 and 3, the networks trained with Bayesian Regulation algorithm shown less sensitivity to the number of neurons in the hidden layer(s) compared to the previous case. In general, see Figure 3, it is evident that neural networks trained with Bayesian Regulation algorithm have a very stable prediction performance regardless of the network structure.

The results of the brake performance prediction using Resilient Backpropagation algorithm are shown in Figure 4. It is obvious that the number of neurons in the hidden layer differently influences the one-layered and two-layered neural networks in the first error interval. Regarding the first error interval (error between 0 and 5 %), the best results have been shown by the neural networks with 3 hidden layers.
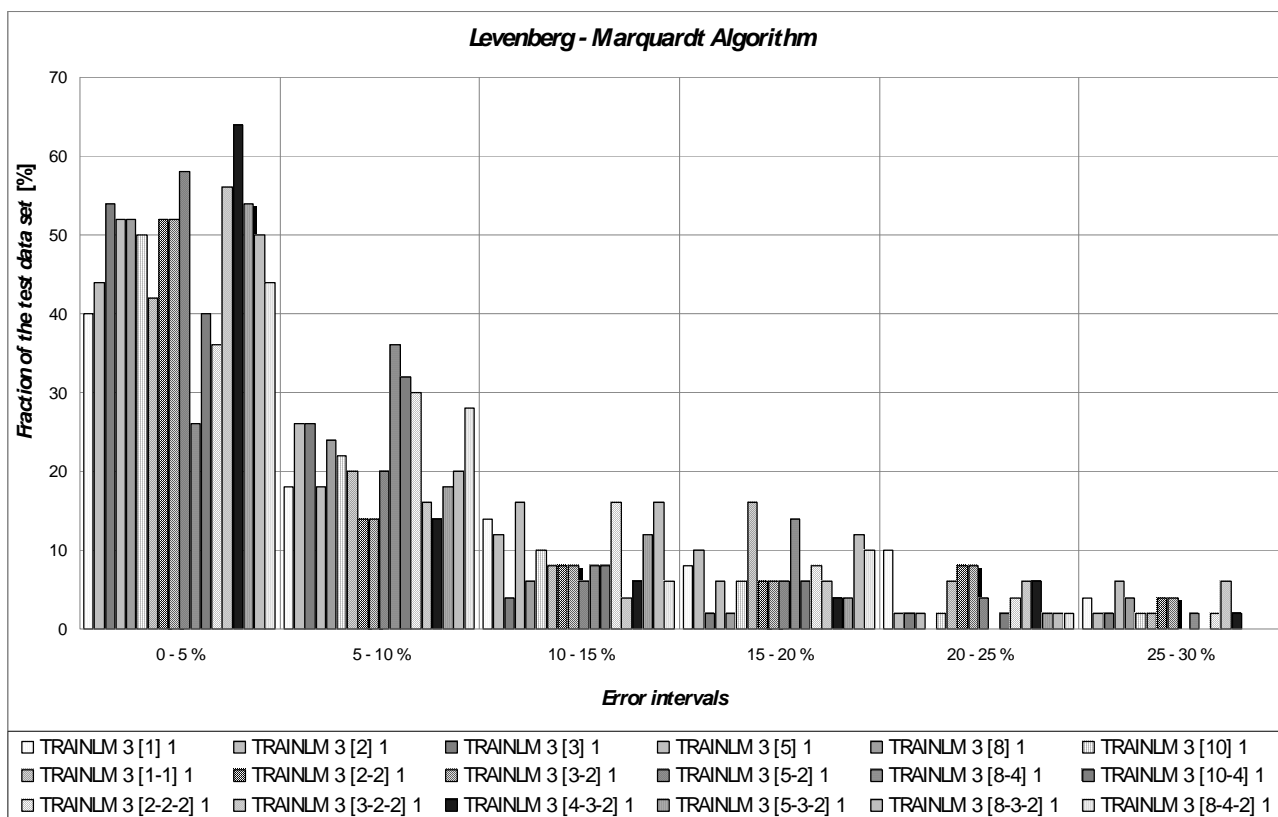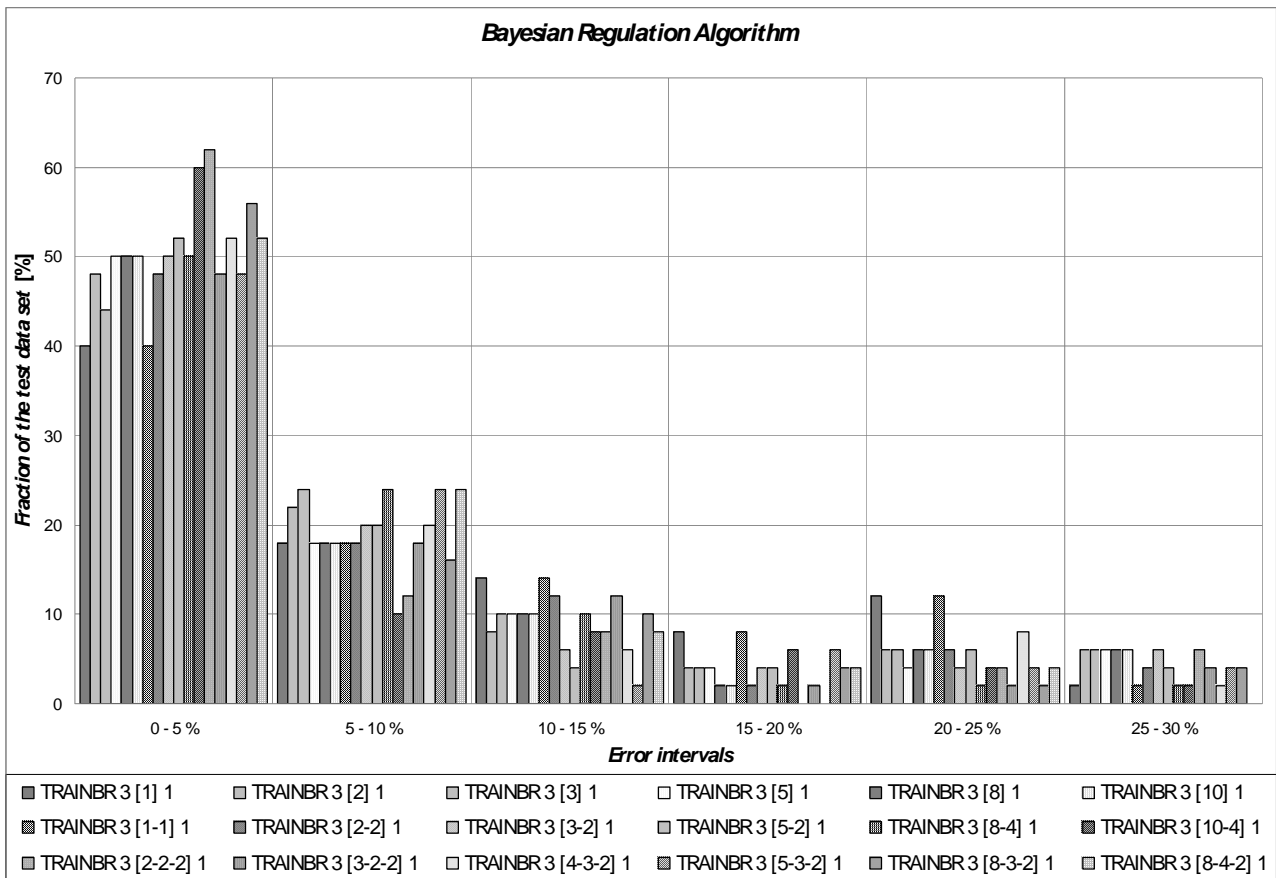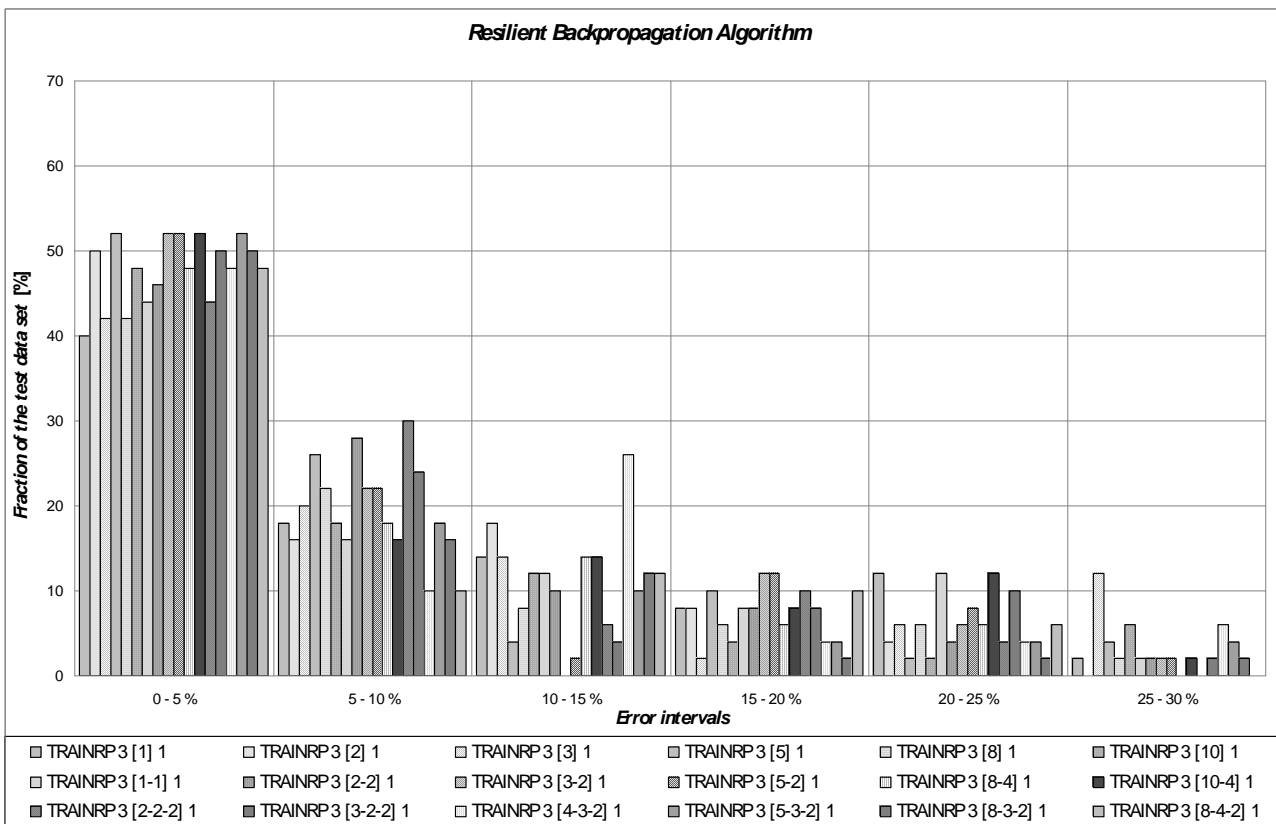

Figure 2. Prediction abilities of artificial neural network trained by Levenberg-Marquardt algorithm

Figure 3. Prediction abilities of artificial neural network trained by Bayesian Regulation algorithm

Figure 4. Prediction abilities of artificial neural network trained by Resilient Backpropagation algorithm

One-layered network structures with one, two and eight neurons in the hidden layer gave results similar to the case of the previous two algorithms. As the number of neurons in the hidden layer increases from 3 to 5 and from 8 to 10, the quality of prediction in the first error interval (0 – 5 %) has been increased. In the second error

interval (5 – 10 %), it can be seen that the number of predicted results decreases by increasing the number of neurons from 1 to 2 as well as from 5 to 10 neurons in the hidden layer. The two-layered and three-layered neural network structures, for the same initial conditions (architectures and learning algorithm), shown stable prediction results. The number of neurons in the three-layered neural network structures has been varied between 2 and 8 in the first hidden layer, over 2 and 4 in the second hidden layer, while that number in the third hidden layer kept constant in all variations (two neurons). The one-layered network architecture, with five neurons in the hidden layer (3 [5]$_1$ 1, see Figure 4, has been show the best prediction results in comparison with all other structures trained with the same learning algorithm.

The neural networks trained by Scaled Conjugate Gradient algorithm show very similar results to those reached by Levenberg-Marquardt algorithm. This training algorithm (see Figure 5) causes higher sensitivity to the number of neurons in the hidden layer of one-layered and especially two-layered structures. Moreover, sensitivity of the neural networks versus the number of hidden layers is almost the same as it was the case with the networks trained by Bayesian Regulation algorithm. According to that, one-layered networks with 1, 2, 8 and 10 neurons in the hidden layer, and two-layered structures with 1, 2, 3, and 10 neurons in the first hidden layer have shown worst prediction result.

Based on the adopted criteria (see Figures 4 and 5), it is evident that networks trained with Scaled Conjugate Gradient algorithm shown slightly less predictive performance. In this case, the best prediction results have been reached by the three-layered neural network structure 3 [3-2-2]$_2$ 1. The distribution of the predicted results over

to the six error intervals using Gradient Descent algorithm is shown in Figure 6. It is obvious that the quality of prediction in the first error interval is influenced by increasing the number of neurons for all types of networks (one, two, and three layered). The percentage of the predicted results in the second error interval (5 – 10 %) was decreased as the number of hidden layers increases.

The network architectures, trained by Quasi-Newton algorithm (trainbfg), have achieved moderate possibilities in prediction of disc brake performance. According to Figure 7, it can be seen that the percentage of predicted results in the first, especially in the second and third error interval, was strongly dependent of the number of hidden layers and/or the number of neurons in each of them. Based on achieved results obtained by training the network structures with this algorithm, it was difficult to select the network architecture with satisfactory prediction performance. Regarding Figure 7, the best results have been achieved by the three-layered network structure 3 [8-3-2]$_3$ 1, while very similar results were reached by the other network architectures.

In order to find out the neural model of disc brake operation, which provides the best prediction results in all tests, 108 different neural models have been analyzed, as it is explained above. A comprehensive summary about this analysis is shown in Table 3.

According to Table 3, the overall prediction performance of the best neural models can be seen for each training algorithm. The three-layered neural network architecture 3 [2-2-2]$_3$ 1, trained by Bayesian Regulation algorithm (BR), has shown the best prediction capabilities (all prediction results have been reached with error not larger than 25 %) over braking regimes investigated in this paper.
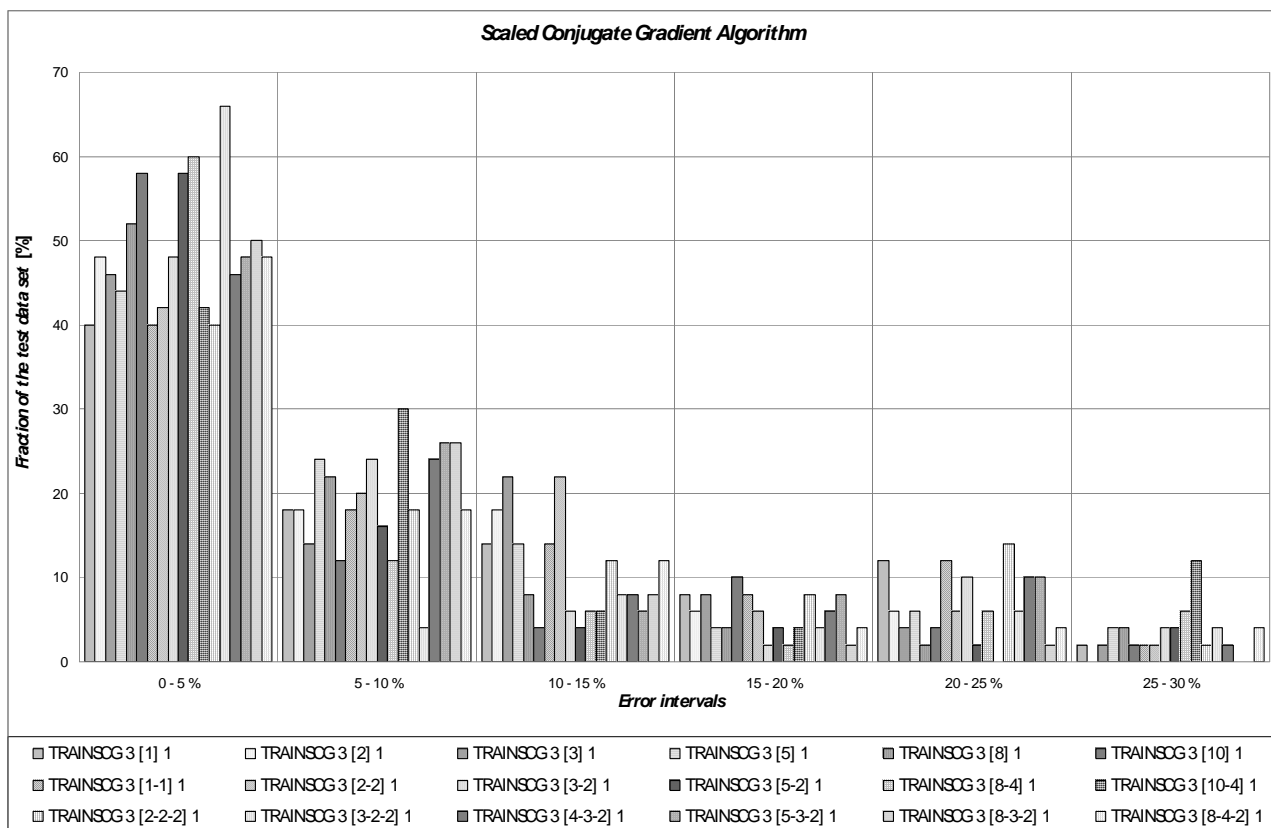

Figure 5. Prediction abilities of artificial neural network trained by Scaled Conjugate Gradient algorithm
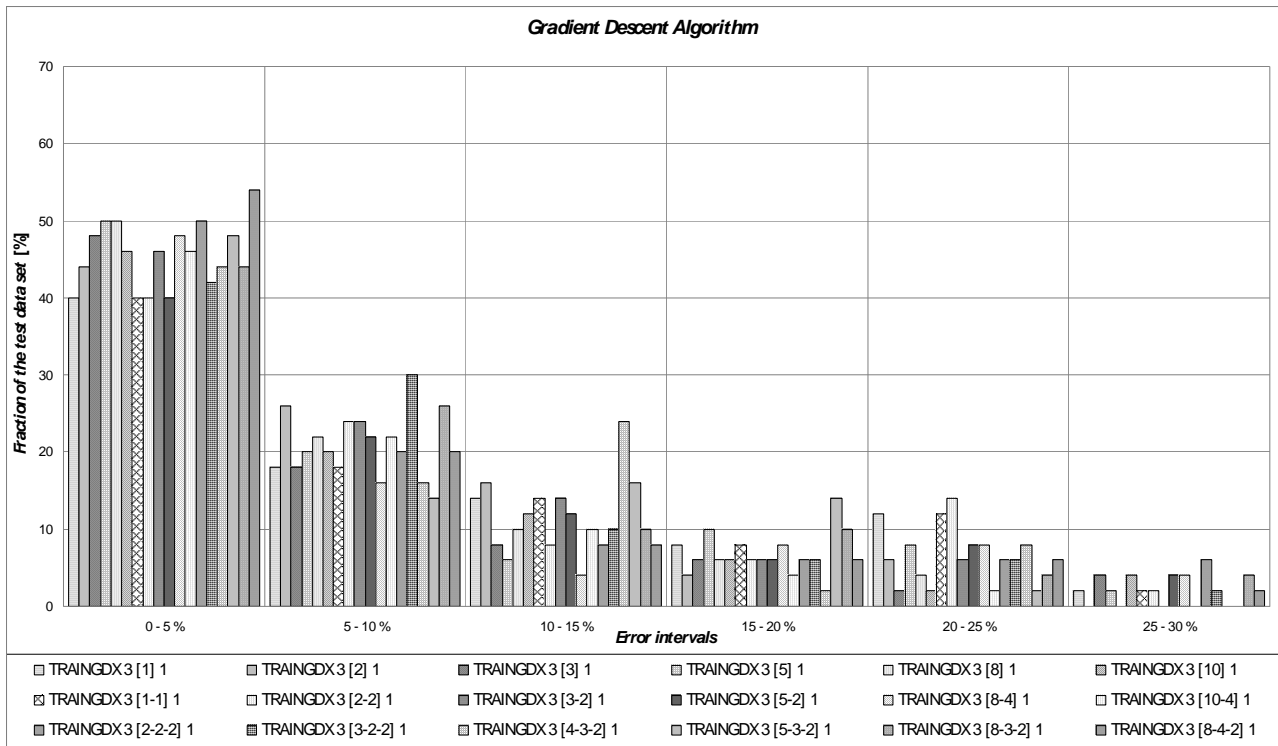
Figure 6. Prediction abilities of artificial neural network trained by Gradient Descent algorithm
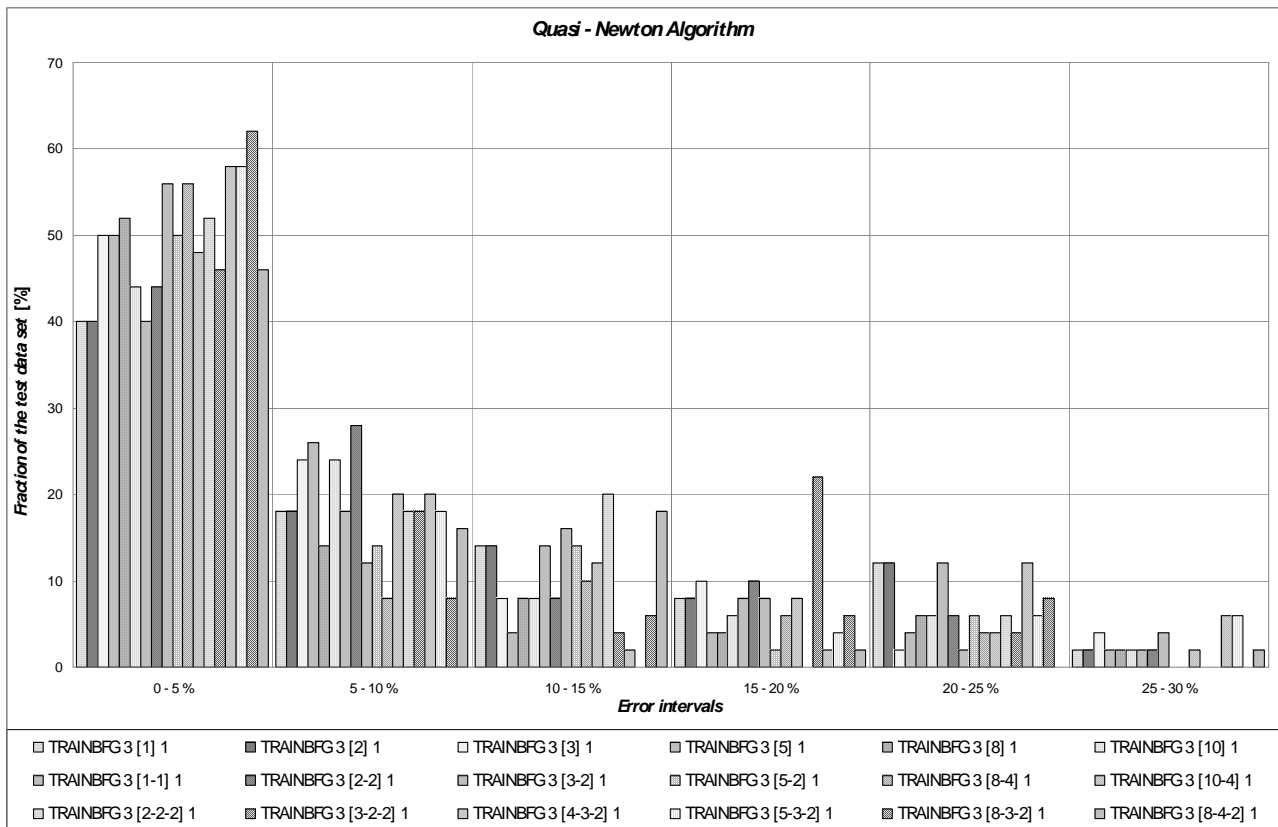

Figure 7. Prediction abilities of artificial neural network trained by Quasi-Newton algorithm

Figure 8 shows a comparison between the six neural network architectures versus their predictive capabilities of disc brake cold, fading, and recovery performance. The comparison between the real values of braking torque and values predicted by these neural network models, under operation condition specified in test cold performance 4, is shown in Figure 8a. Figure 8a shows

that three-layered network architecture with two neurons in each of the hidden layers, trained by Bayesian Regulation algorithm (BR), well generalized input/output relationships compared to other neural network architectures. Moreover, braking torque prediction by network architectures trained with Scaled Conjugate Gradient (SCG) and Gradient Descent

Table 3. Comparison of neural network prediction performance versus error intervals

| Neural models	Error intervals [%]					
	0 – 5 %	5 – 10 %	10 – 15 %	15 – 20 %	20 – 25 %	25 – 30 %
TRAINLM 3 [8-3-2]₃ 1	50.0	20.0	16.0	12.0	2.0	0.0
TRAINBR 3 [2-2-2]₃ 1	50.0	26.0	8.0	6.0	10.0	0.0
TRAINRP 3 [5]₁ 1	52.0	26.0	4.0	10.0	2.0	4.0
TRAINSCG 3 [3-2-2]₃ 1	66.0	4.0	8.0	4.0	6.0	4.0
TRAINGDX 3 [8-4-2]₃ 1	54.0	20.0	8.0	6.0	6.0	2.0
TRAINBFG 3 [8-3-2]₃ 1	62.0	8.0	6.0	6.0	8.0	0.0

(GDX) algorithms was also on acceptable level compared to real values of braking torque. It is interesting that for the initial speed range between 20 and 80 km/h, neural network architecture trained by Quasi Newton (BFG) training algorithm well generalized the trend of braking torque changes only, but prediction error was substantially higher than the other network architectures. The error level of results predicted by neural networks trained by Resilient Backpropagation algorithm is similar with the results obtained by the network architecture trained by Quasi Newton (BFG) algorithm (see Figure 8a). As it can be seen from Figure 8a, prediction results obtained by the neural model obtained by training with Levenberg-Marquardt algorithm (LM), shown the highest fluctuations compared to real ones for all range of initial speed (the error versus real braking torque is low only for initial speed value of 60 km/h).

In the case when the brake interface temperature has a dominant influence on brake performance (fading test),

for the application pressure of 30 bar and initial speed of 90 km/h, predictions of braking torque were visibly worse than in the cold performance test (see Figure 8b). The all neural network structures were tested with results that belong to test fading 2 (according to Table 2). Comparing Figures 8b and 8a it can be concluded that temperature in the contact of friction pair has significant influence on the disc brake performance. That is why, the prediction of disc brake performance under this operation conditions was very challenged for analysed neural models.

All considered neural network architectures, except networks trained by LM and BFG algorithms, have shown similar prediction abilities. The neural models well predicted the general trend of changing of braking torque. For the range of brake interface temperature between 200 – 275 °C, the error between the real and predicted braking torque values was the biggest for all considered neural networks.

Figure 8c is related to the prediction of disc brake recovery performance versus change of the application
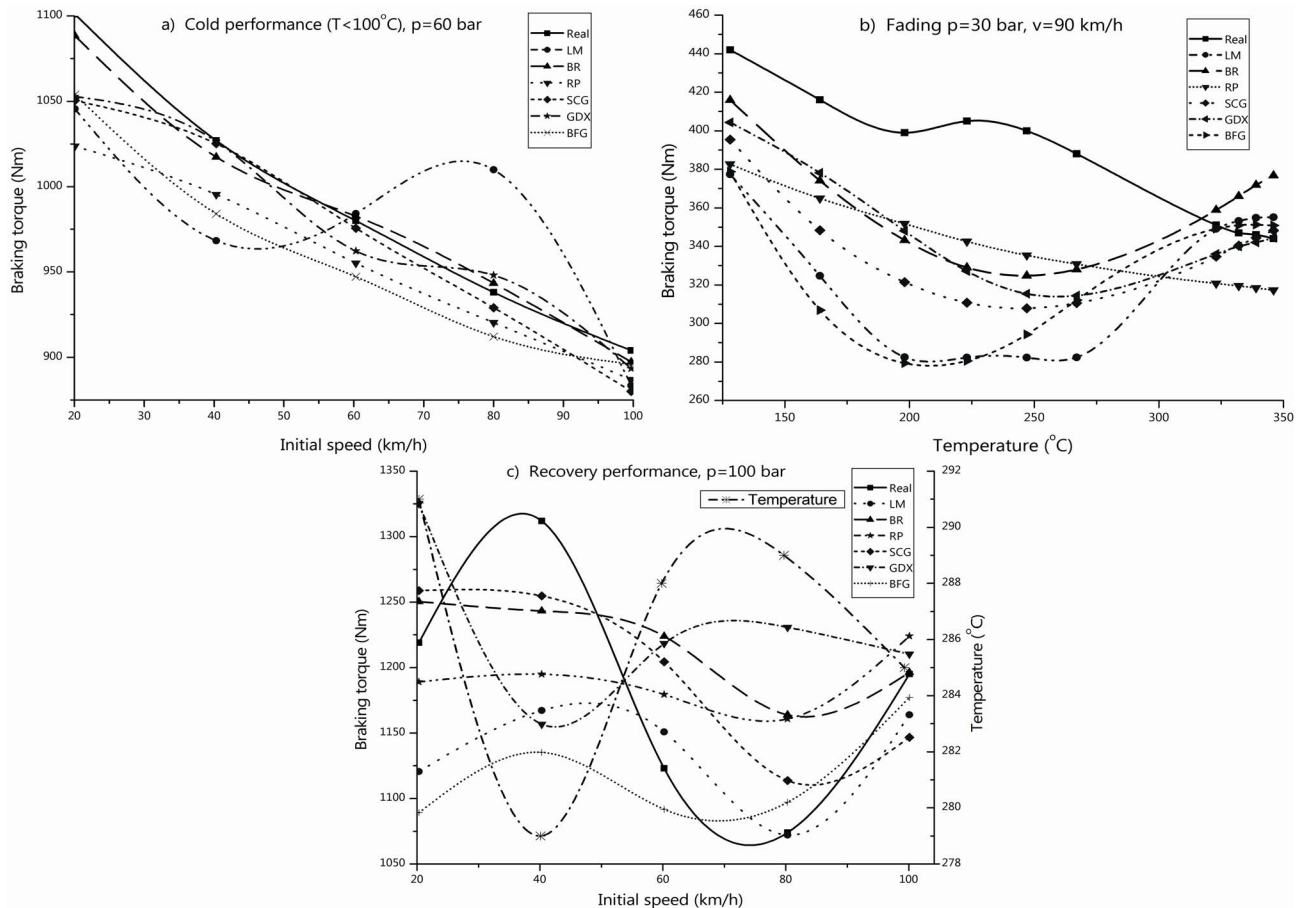
Figure 8. Comparison between the real and predicted cold, fade, and recovery performance of disc brake

pressure, initial speed, and brake interface temperature. A comparison between the real and predicted braking torque is shown in Figure 8c. It is evident that all considered neural network architectures have shown insufficient performance in terms of predicting the braking torque changes. Predictions obtained by the neural network trained with GDX algorithm are particularly imprecise. For the initial speed, values between 60 – 100 km/h the network architecture, trained by Quasi Newton (BFG) algorithm, achieved the best prediction results (see Figure 8c). Three-layered neural network architecture 3 $[3-2-2]_3$ 1 trained by SCG learning algorithm has achieved the best prediction performance for the initial speed range from 20 – 60 km/h. Comparing Figures 8c and 8b, it can be concluded that high temperature load in the contact of friction pair, has affected the disc brake performance. That is why the neural models abilities had to be improved in order to be able to predict these complex changes in disc brake performance.

4. CONCLUSIONS

This investigation has demonstrated that artificial neural networks can model complex non-linear interrelations between brake input/output variables. It was also shown that there is a complex synergy of influences between different architectures of the neural networks and learning algorithms on the final neural model prediction abilities. The quality of prediction of disc brake performance has been tested versus three input parameters which defined disc brake operation conditions (initial speed, application pressure and brake interface temperature). The 108 neural models were investigated. The neural models have been developed with inherent abilities to predict the disc brake performance under different operation conditions (cold, fade, and recovery performance). In order to find the optimal neural model, the trail and error method has been used to evaluate network prediction performance. The best prediction results, related to all three kinds of tests, were obtained by the three-layered neural network architecture 3 $[2-2-2]_3$ 1 trained by Bayesian Regulation (BR) training algorithm. Due to high fluctuation in the disc brake performance, it was shown that is difficult to develop a unique neural model able to predict these complex changes in different braking regimes. Although done on limited number of training and test data, in this paper is shown that, besides the neural network architecture, used learning algorithm, transfer functions or range and distribution of input/output data, greatly affecting the network's generalization capabilities.

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РАЗВОЈ НЕУРОНСКОГ МОДЕЛА РАДА ДИСК КОЧНИЦЕ

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Квалитет вештачких неуронских модела претежно зависи од правилног избора архитектуре вештачке неуронске мреже, односно алгоритма учења, функције преноса, опсега и расподеле података коришћених за обуку, валидацију и тестирање. Основни циљ овог рада се односи на истраживање како архитектуре вештачких неуронских мрежа утичу на успешност предвиђања тј. способност генерализације мрежа за исти сет података за обуку и тестирање. Комплексни поступак развоја вештачког неуронског модела је демонстриран на примеру диск кочнице. Моделиран је утицај радних услова диск кочнице (притисак активирања, почетна брзина и температура) на њене максималне перформансе као и перформансе опадања и обнављања ефикасности. Вештачки неуронски модел је развијан кроз истраживање на који начин синергија различитих параметара мреже, попут алгоритма учења, функције преноса и броја неурона у скривеним слојевима, утиче на способности неуронског модела да предвиди перформансе диск кочнице. У овом раду је показано да комплексне нелинеарне зависности између посматраних улазних и излазних параметара могу бити моделиране одговарајућом анализом и подешавањем параметара вештачке неуронске мреже.